System Identification of UAV under an Autopilot Trajectory Using ARX and Hammerstein-Wiener Methods

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ABSTRACT

The need of an efficient mathematical model that characterizes the Aircraft system dynamics is essential for implementing an autopilot system, control algorithms, and other applications. The challenge of system identification is to predict the parameters of the system and construct a model that can estimate the system behavior under both normal inputs and disturbance.

One of the main problems in system identifications is defining the input signal for the system. For aircrafts system identification was done using a test signal that take into consideration the allowed range of the inputs (usually Euler angles and their rates). The main contribution in this paper is in giving more realistic inputs using the adaptive autopilot that control the aircraft trajectory

In this paper, system identification of lateral and longitudinal dynamics will be presented for an ARF-60 UAV using both linear and nonlinear estimation methods. The estimation methods are Autoregressive with exogenous model (ARX) method for linear estimation, and Hammerstein-Wiener method for nonlinear estimation. Moreover, a comparison will be made between the model and original system. The input trajectory of the system defines how strong the estimation will be; for example, a straight line trajectory will not give enough data to construct the estimated model. The orders of each estimation is given and its coefficients.

1. INTRODUCTION

The rise of using digital components in different components of the UAV reflects the need of an efficient discrete-time model. In this paper the methods of estimation will be discussed, the results, and finally a comparison of the results.

Autoregressive with exogenous (ARX) model is an estimation method that uses general least square theory to estimate the system dynamics. It gives the number of zeros and poles of the system along with the response delay.

Hammerstein-Wiener decomposes the relation between the input and output with a linear system that can be presented with the number of zeros and poles of the system. The input signal for the linear block is a transformed signal of the input nonlinear block, and the output is a nonlinear function of the linear system output.

When using Hammerstein-Wiener method for system identification the computation of the nonlinear input and output functions of the linear block was done after predefining its orders.

1.1. Nomenclature

[P Q R]	presents Euler angles rates
[U V W]	presents the ground speeds of the UAV
[Na Nb Nk]	presents the orders of the zeros, poles, and response delay for ARX model
[Nb Nf Nk]	presents the orders of the zeros, poles, and response delay for Hammerstein-Wiener model

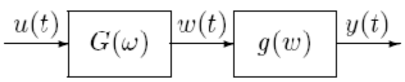
2. BACKGROUND

Nonlinear system identification is a challenging task due to the modeling the nonlinearities in an efficient way. Then the system model structure is known, nonlinear regression and their coefficient parameters are given in linear-in-the parameter model.

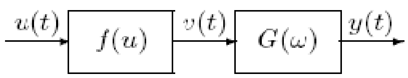
$$\dot{x} = \Phi(x)\theta$$

Where $x \in \Re^n, \Phi(x)$ nonlinear regression matrix as a function of known model structure and $\theta \in \Re^m$.

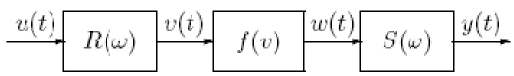
Then the linear-in-the-parameter model may not be driven sufficiently well various modeling techniques may be applied. In this paper we will focus on Hammerstein-Weiner method.



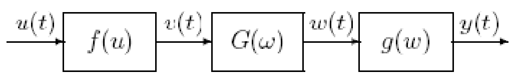
(a) Wiener system



(b) Hammerstein system



(c) Hammerstein-Wiener System



(d) Hammerstein-Wiener system

Figure 1. *Various Hammerstein and Wiener system topologies.*

Input and output nonlinearities are represented by

$$f(u) = \sum_{n=1}^{q_f} \lambda_n u^n$$

$$g(w) = \sum_{n=1}^{q_g} \mu_n w^n$$

For Hammerstein-Wiener system depicted in Fig. 1.d. The linear system is represented by

$$G(\omega) = \frac{W(\omega)}{V(\omega)}$$

3. THE NONLINEAR MODEL OF THE UAV SYSTEM

The estimations were based on a nonlinear six degree of freedom (6 DOF) model of the UAV system. A modified version of the Aerosim model was used. Aerosim is a Matlab/Simulink library that has a 6 DOF model of UAV. This nonlinear model used in this paper has coupled nonlinear subsystems that model the real system dynamics. The modification of the Aerosim block is the autopilot blocks, which analyze the states of the aircraft and produce a roll angle command that controls the path of the aircraft after defining the wanted trajectory.

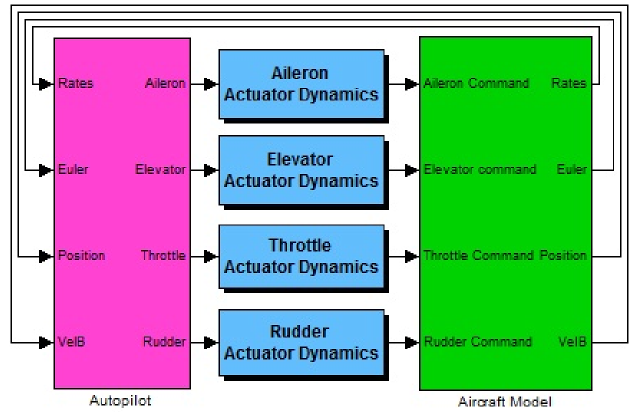


Figure 2. *Nonlinear System with Autopilot Command.*

3.1. Input Trajectory

In order to have a good estimated model, input trajectory (Fig. 3) should give the parameters of the system (aileron, elevator, throttle and rudder) a sufficient excitation that guarantees enough experimental data so that system identification can take those data and construct its models. In the literature, system and model identification is done with some test signals that may not reflect a reasonable input. Here, we try to give a more realistic input according to the trajectory that we define using the autopilot.

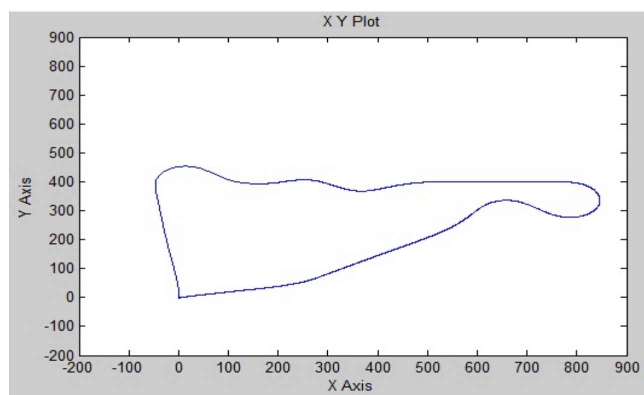
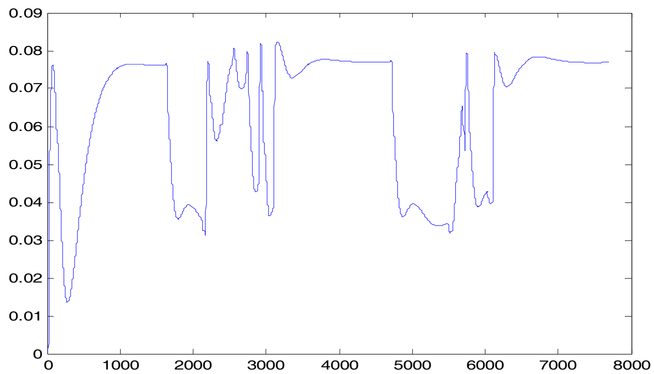


Figure 3. *Input Trajectory Path.*

The trajectory was controlled using the autopilot block shown in Figure (1). The reason for choosing such a trajectory as a test input is the turns it takes at (0, 0), (0, 400), and (800, 300). Since the Autopilot command controls the roll angle, initially the rudder and roll changes to follow the line from the origin to (0,400). Later on, the UAV takes a straight line to saturate its parameters, and then it takes a turn at (800,300) heading to the origin. The trajectory took 73 seconds and estimation was done with 0.01 seconds sampling period.

As an example the resultant Elevator and Aileron signals in radians/sample were as follows:



(a) Elevator deflection input

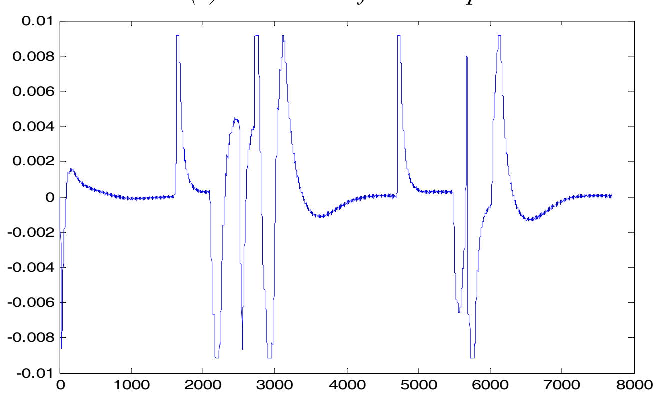


Figure 4. *Elevator and Aileron Input signals*

3.2. ARX Model

Using the ARX Model for system identification, analysis of measured data revealed the optimal system order for both lateral and longitudinal commands. Transfer functions and associated system orders are

Lateral Command:

Elevator Input to

- U orders: N_a=1 N_b=1 N_k=1
- W orders: N_a=2 N_b=1 N_k=1
- Q orders: N_a=5 N_b=3 N_k=3
- Pitch angle orders: N_a=3 N_b=1 N_k=1

Throttle Input to

- U orders: N_a=1 N_b=1 N_k=1
- W orders: N_a=3 N_b=1 N_k=1
- Q orders: N_a=1 N_b=1 N_k=10
- Pitch angle orders: N_a=1 N_b=1 N_k=1

Longitudinal Command

Aileron Input to

- V orders: N_a=10 N_b=4 N_k=4
- P orders: N_a=10 N_b=10 N_k=1
- R orders: N_a=2 N_b=1 N_k=2
- Roll angle orders: N_a=2 N_b=2 N_k=1

Rudder Input to

- V orders: N_a=2 N_b=1 N_k=1
- P orders: N_a=10 N_b=10 N_k=1
- R orders: N_a71 N_b=6 N_k=10
- Roll angle orders: N_a=10 N_b=9 N_k=1

For example the difference between the original output (Black) and estimated output (Yellow) for the Elevator to Q model is shown below in Figure 5. The estimation matching was 43%.

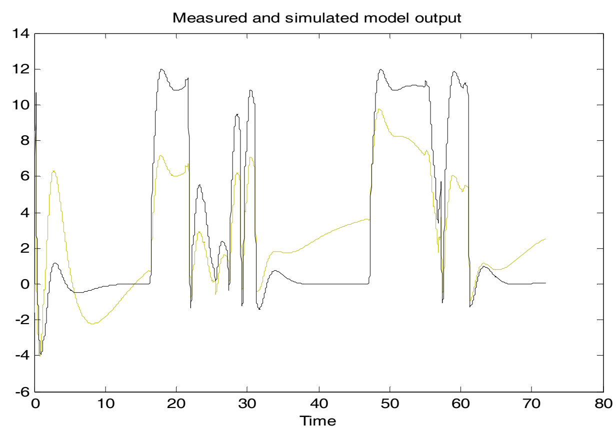


Figure 5. *Q Original and Estimated Output from the Elevator Input with Estimation matching 43%.*

In general the performance of the estimated model using ARX method was not reliable. It can be seen from Figure 5 that the elevator input changes vertically for both models at almost the same time, but it does not give them enough amplitude every time.

3.3. Hammerstein-Wiener Model

Using the Hammerstein-Wiener Model, and the Adaptive Gauss-Netwon for system identification, the orders of the middle linear block were chosen to be for both lateral and longitudinal commands as N_b=2 N_f=3 N_k=1.

In general the Hammerstein-Wiener model gave a better estimation in the transient and the sudden changes in the steady state, and that can be clear in Figure 6.

After using the Hammerstein-Wiener model the difference between the original output (Black) and estimated output

(Gray) for the Elevator to Q model has been increased to 82% and it is shown below:

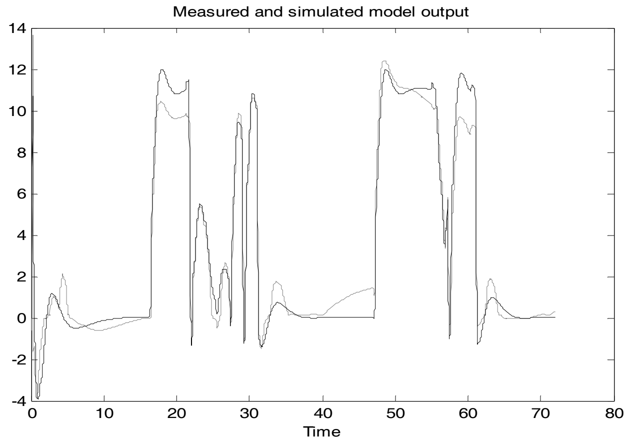


Figure 6. Q *Original and Estimated Output from the Elevator Input with Estimation matching 82%.*

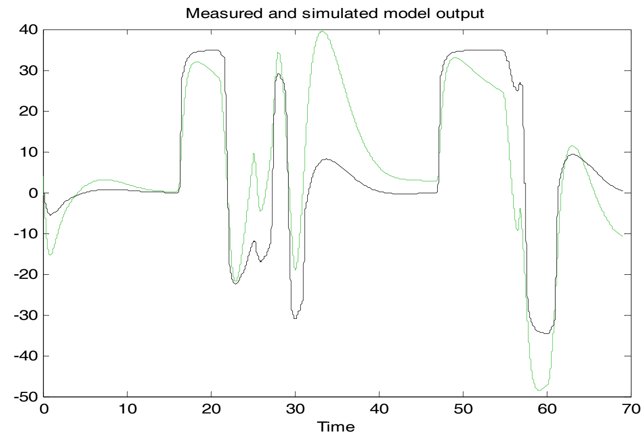
The range of matching between the actual system model and the estimated models has increased to up to 90% when using Hammerstein-Wiener model for the elevator signal. However, models using the throttle input signals did not show major improvement in nonlinear model. This shows the difficulty of estimating the throttle to ground speeds, and the pitch angle. The latter model is performing well for everything except the lateral (throttle) parameter.

3.4. ARX Model for Euler Angels with disturbance

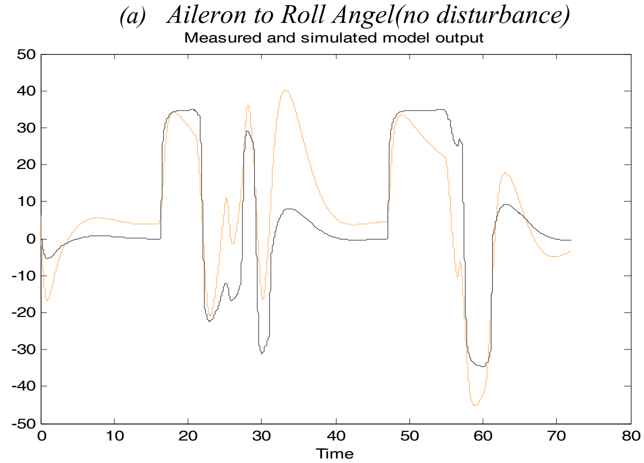
Disturbance effect is studied for the models. Using the same estimation model orders from the ARX model for the Euler angles, system identification was carried out with a disturbance added to each signal.

The estimated model was almost the same. For example, Figure 7 shows the Aileron to roll angel output for the normal Aileron signal and disturbed one; it can be seen that there is not much difference; the matching with the original model was reduced from 36.81% to 35.34% after testing the disturbed signal.

With a larger disturbance added to the input the estimated model matching percent goes down with higher percentages.



(a) Aileron to Roll Angel(no disturbance)



(b) Aileron to Roll Angel with disturbance input

Figure 7. *Actual and Estimated Roll Angle Output*

4. CONCLUSIONS

This paper showed the less matching between the original and estimated models when using a more realistic trajectory as a test input signal for system identification.

When using the ARX model. This shows its incapability of capturing the transient states of the system. However, in the steady state the ARX model gives a better estimation and that can be seen after graphing the model and its ARX estimation.

The nonlinear Hammerstein-Wiener estimation has given a powerful result when estimating the system. When using the Adaptive Gauss-Newton method and a default linear block orders [2 3 1].

5. ACKNOWLEDGMENTS

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6. REFERENCES

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